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A cross-entropy method applied to the In-core fuel management optimization of a Pressurized Water Reactor

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ABSTRACT

The In-Core Fuel Management Optimization (ICFMO) is a prominent problem in Nuclear Engineering. In the present paper, the application of the Cross Entropy (CE) method to the ICFMO is described. The CE method was initially developed for rare event simulation, and adapted to combinatorial and continuous optimization. Unlike the several metaheuristics biologically or physically inspired that have been applied to the ICFMO, the CE is an algorithm based on statistics and information theory, specifically on the minimization of the Kullback-Leibler divergence (or cross entropy). Notwithstanding the high level theory underlying the algorithm, its implementation mainly comprises the sampling of candidate solutions at each iteration with an update of parameters for generating the random sample in the next iteration given by the analysis of an elite group within the sample. Thus, it is possible to drive the algorithm to optimal or near optimal solutions iteratively. The CE algorithm was applied to the optimization of the 7th cycle of Angra 1 Nuclear Power Plant, in Brazil. The results compare favorably to other algorithms such as Genetic Algorithm, Population Based Incremental Learning, as well as Particle Swarm Optimization under the same conditions of simulation.

1. Introduction

The In-Core Fuel Management Optimization (ICFMO) or Loading Pattern (LP) Optimization is a prominent real-world problem in Nuclear Engineering whose goal is to determine the LP for producing full power within adequate safety margins (Levine, 1987) in Nuclear Power Plants (NPPs). According to Stevens et al. (1995), the high complexity of the ICFMO is characterized by a large number of feasible solutions, a large number of sub-optimal solutions, disconnected feasible regions, high dimensionality, complex and time-consuming evaluation functions that involves Reactor Physics calculations (Dudersdadt and Hamilton, 1976), as well as approximation hazards.

Due to the high complexity and the combinatorial characteristics of the ICFMO, classical approaches such as gradient-based optimization methods are not appropriated to its solution. Conversely, several metaheuristics or generic heuristic methods (Taillard et al., 2001) have been successfully investigated for application to the ICFMO such as Simulated Annealing (Kropaczek and Turinsky, 1991), Genetic Algorithms (GA; Poon and Parks, 1992; Chapot et al., 1999), Ant Colonies Optimization (ACO; Machado and Schirru, 2002), Population Based Incremental Learning (PBIL; Machado, 2005), Artificial Bee Colonies (ABC; de Oliveira and Schirru, 2011), and Particle Swarm Optimization (PSO; Meneses et al., 2009a).

Whereas the application of such methods to the ICFMO increases worldwide, demonstrating that metaheuristics are currently the state-of-art for the solution of that problem, a statistical and information theoretical method known as Cross Entropy (CE; Rubinstein and Kroese, 2004) developed for rare event simulation, combinatorial and continuous optimization (Rubinstein, 1997, 1999) may now open a new path to the LP optimization.

The core idea of the CE algorithm comes from the estimation of rare events in complex stochastic networks by an adaptive algorithm (Rubinstein, 1997). Rubinstein (1999) adapted the algorithm for application to Combinatorial Optimization Problems (COPs) using a stochastic estimation version instead of the well-known deterministic formulation. Thus a similar solution framework could be used for COPs. In this sense, finding optimal or near-optimal solutions in NP-Hard combinatorial problems (a

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deterministic point-of-view) can also be seen as an estimation problem of rare events occurrences (a stochastic point-of-view).

Schlünz et al. (2014) applied a multiobjective CE method to a nuclear research reactor outperforming engineering solution and heuristic rules. In the present paper, the CE algorithm is reviewed and applied to the ICFMO (CE-ICFMO) of an NPP. Computational experiments were performed with the simulation of the 7th cycle of Angra 1 NPP, in Brazil. The results reported in the present article compare favorably in relation to algorithms such as GA, PBIL and PSO.

The remaining of the present article is organized as follows: Section 2 is related to the ICFMO of the Angra 1 NPP; Section 3 presents the CE method; the results are described in Section 4; in Section 5 we discuss the results; concluding remarks are made in Section 6.

2. In-core fuel management optimization of Angra 1 nuclear power plant, in Brazil

Angra 1 NPP is a 626 MW 2-loop PWR located at Rio de Janeiro State, Brazil, operated by Eletronuclear, whose core is composed by 121 FAs. The Reactor Physics code RECNOD is a simulator for Angra 1 NPP (Chapot et al., 1999; Chapot, 2000). RECNOD is a nodal code based on the works described by Langenbuch et al. (1977), Liu et al. (1985), and Montagnini et al. (1994), applied to optimization surveys in several works (e.g. Chapot et al., 1999; Meneses et al., 2009a, 2010).

The octant-symmetry for the RECNOD simulation is depicted in Fig. 1. In our simulations, FAs of the symmetry lines (quartets) are not exchanged with elements out of the symmetry lines (octets). In addition, the central element is not permuted, which yields $10! \times 10! \cong 1.3 \times 10^{13}$ possible permutations. Table 1 exhibits the burnup and k_{inf} values for the basic LP of RECNOD code depicted in Fig. 1 (Chapot, 2000; Oliveira and Schirru, 2011).

The nuclear parameters yielded by the code are, among others, the Maximum Assembly Relative Power (P_{rm}) and the Boron Concentration (C_B). The value of P_{rm} is used as a constraint related to safety. For a maximum required radial power peak factor $F_{XYmax} = 1.435$ for Angra 1 NPP, the calculations yield a correspondent $P_{rm} = 1.395$. Any LP with $P_{rm} > 1.395$ is infeasible in the sense of the safety requirements.

C_B yielded by the RECNOD code is given at the equilibrium of Xenon, which reduces the computational cost of the processing, without impairing its validity for optimization purposes. Chapot (2000) demonstrated that it is possible to extrapolate and predict the cycle-length based on the C_B at the equilibrium of Xenon, in such a way that 4 ppm are approximately equivalent to 1 Effective Full Power Day (EFPD). In addition, 1 more EFPD is equivalent to a profit of approximately hundreds of thousand dollars. Since previous works' results were obtained at the equilibrium of Xenon, the same condition was used in the present work.

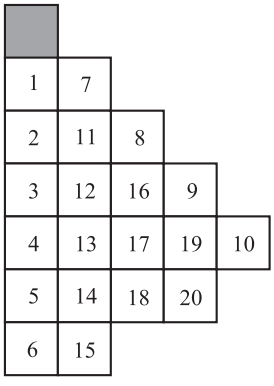

Fig. 1. Representation of the 1/8 symmetry model: except for the central FA in grey, all of the 20 FAs are permuted. FAs along the symmetry lines (1–10) are not permuted with FAs that are not along the symmetry lines (11–20) and vice versa.

Table 1
Burnup and k_{inf} values for the FAs in Fig. 1.

FA	Burnup	k_{inf}
1	9603	1.069
2	13,045	0.906
3	7882	1.087
4	13,006	0.906
5	0	1.187
6	13,012	0.906
7	14,650	1.037
8	8622	1.079
9	13,181	0.903
10	0	1.193
11	14,068	1.026
12	13,115	0.906
13	13,135	0.904
14	0	1.188
15	0	1.194
16	11,404	1.050
17	7873	1.099
18	0	1.191
19	0	1.188
20	13,285	0.907

The objective function of the ICFMO related to Angra 1 according to the parameters given by RECNOD is

$$\text{minimize} \quad \frac{1}{C_B} \tag{1}$$

subject to

$$P_{rm} \leq 1.395. \tag{2}$$

The aggregated *fitness function* (considering that the values of P_{rm} are always greater than the reciprocal of the Boron Concentration) is

$$Fitness = \begin{cases} \dfrac{1}{C_B}, & if \;\; P_{rm} \leq 1.395 \\ P_{rm}, & otherwise \end{cases}, \tag{3}$$

which was the fitness used by Meneses et al. (2009a, 2009b, 2010).

3. The cross-entropy method

3.1. The CE algorithm

The simulated Cross-Entropy method or Cross-Entropy method (CE; Rubinstein, 1999; Rubinstein and Kroese, 2004) is a stochastic algorithm initially motivated in the area of rare event simulation (Rubinstein, 1997) which was later adapted to the optimization of COPs (Rubinstein, 1999). The CE algorithm has interesting characteristics such as generality and flexibility. In fact, applications of the method in several areas corroborate the success of the algorithm, such as in telecommunication systems (de Boer et al., 2004) and vehicle routing (Chepuri and Homem de Mello, 2005).

Each iteration of the CE method comprises basically two steps (Fig. 2). In the first step, a data sample (e.g. vectors or trajectories) is generated according to a random mechanism. In the second step, the mechanism's parameters are adjusted in order to generate a better sample in the next iteration.